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The role of green networks for environmental innovation in European regions

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Abstract
This paper investigates the role of green research networks in green innovation capabilities (proxied by green patents) in European regions. Our hypothesis is based on the idea that cross-border collaboration facilitates the diffusion of knowledge, thereby favouring the green innovation of the regions belonging to the network. We exploit information contained in the European Framework Programmes by looking at the role of intra and extra-regional collaborations and at the diversity of institutional partners. We find that both intra and extra regional collaborations matter for green innovation, although external knowledge appears to be more relevant. We also find a positive effect of firms in the network, of projects involving both firms and universities and a non-linear effect of network heterogeneity. We discuss the implications of the results for green innovation policies.

Keywords Green innovation · Green patents · Knowledge diffusion · Networks · European regions

JEL Classification O33 · Q55 · R11 · C2

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1 Introduction

In an era of unprecedented environmental crises, environmental (or green) innovation (EI) plays a critical role in sustaining the green transition. The European Union has responded to this emergency by taking massive measures to decrease its carbon footprint and enhance sustainability through the European Green Deal (Fetting, 2020).

One of the core components of the Green Deal is the 'Fit for 55%' package, a set of proposals introduced following the Paris Agreement in 2015.[1] The package aims to reduce CO2 emissions by 55% compared to 1990 levels by the end of 2030 and to achieve climate neutrality, or net zero emissions, by 2050. The ultimate goal of the Fit for 55% package is to make Europe the world's first climate-neutral continent by 2050. Two key elements of the renewed EU strategy to fight climate change are the extension and revision of the European Emissions Trading System (EU ETS) and the introduction of the Carbon Border Adjustment Mechanism (CBAM). The EU ETS cap reduction aims to decrease the number of emission allowances available, while the CBAM is designed to prevent carbon leakage by applying a carbon price on imports of certain goods from outside the EU, ensuring that European companies are not disadvantaged by climate policies (Böning et al., 2023).

In the short term, these measures are likely to increase production costs for firms as they should internalize the external costs of pollution. This internalization process means that firms will have to pay for the environmental damage they cause, which can initially result in higher costs and reduced profitability. In the long term, to maintain international competitiveness, companies should focus on improving their innovation capabilities and increasing R&D investments. By enhancing their ability to innovate, firms can develop new technologies and processes that reduce emissions and improve efficiency, thereby mitigating the negative impacts of the greening measures. This emphasis on innovation is critical for the green transition, as it enables companies to adapt to new regulations and avoid the transition costs. Such a transition can be achieved through innovation and cooperation among EU members.

Given the unique nature of green technologies and the specialised knowledge required for environmental innovation (EI), the literature emphasises that firms cannot act in isolation (Cisneros et al., 2023). They need to seek new knowledge and expertise beyond their own boundaries by collaborating with other actors. Networks play a crucial role also because the EU is financing knowledge-generation with its own resources which are not distributed evenly across regions due to uneven regional capabilities and this risks to exacerbate regional disparities. Networks between regions with different innovation capabilities can help to disseminate green knowledge and avoid the concentration of green innovation. With these aims, the European Commission has been actively promoting and supporting cooperative initiatives in research and innovation through multi-annual and multi-thematic Framework Programmes (FP). These programmes involve significant public investments aimed at generating and diffusing knowledge, thus fostering economic growth and convergence (Balland et al., 2018; Meliciani et al., 2022). They finance joint projects that aim to create networks among all institutional research sectors, including firms, uni-

[1] The Paris Agreement is an international treaty was adopted at the UNFCCC (COP21) in Paris.

versities, and public research centers. The core objective of this strategy is to generate new knowledge and implement it in business practices and production processes, thereby enhancing the performance of firms, regions, and countries, and making them more competitive in the global market.

Although there is a growing body of literature examining the impact of participation in the EU FPs on knowledge transfer (Di Cagno et al., 2014; Hoekman et al., 2013; Maggioni et al., 2007), to the best of our knowledge there is no empirical evidence on how green networks may affect the green innovation capacity at the regional level. We try to fill this gap by investigating the role of green research networks in enhancing green innovation capabilities within European regions. First, we test the hypothesis that collaboration within these networks promotes green innovation in the regions involved. Second, we explore whether collaboration beyond regional boundaries facilitates the diffusion of knowledge thus promoting EI. Third we look at the role of the heterogeneity of participants in the network for green innovation. Our hypotheses build on the recent literature which has identified some specific features characterizing EIs: (i) the knowledge required for the implementation of clean technologies is more complex (Barbieri et al., 2020), (ii) more "codified" than that required for innovations of standard technologies (Cainelli et al., 2015) and, above all, (iii) environmental innovations require more heterogeneous sources of knowledge than other innovations (Horbach et al., 2013). These three aspects necessarily lead to the need to pursue a collaborative innovation process (Fabrizi et al., 2018, 2024; Ghisetti et al., 2015). Awareness has emerged that EIs with a heterogeneity of partners is crucial because the ecological transition requires diversified knowledge that can be produced by inter-organizational learning (Albort-Morant et al., 2016). Moreover, the interaction and hybridisation between three institutional spheres—'industry', 'university' and 'government' (Triple Helix, Etzkowitz & Leydesdorff, 2000)—is particularly valuable for green innovation considering the role of regulation in directing green efforts and the necessity of adopting a systemic approach. The synergies among various actors in the network are critical for enhancing innovation capacity (Ghisetti et al., 2015) however these interactions might also present challenges due to the diverse knowledge bases and objectives of each actor, as highlighted by Foray and Lissoni (2010). In addition, technological differences between team members can hinder knowledge exploitation and reduce the impact of inventions by acting as conflict and learning barriers (Lovelace et al., 2001). Due to the different technological knowhow, increasing the heterogeneity of actors in a team may lead to diminishing marginal returns (Huo et al., 2019). Whether and to what extent the heterogeneity of networks has a positive impact on green innovation is, therefore, an empirical question that, to the best of our knowledge, has not been investigated so far. Shedding light on this aspect is important for designing appropriate policies for the formation of networks that are more effective to stimulate green innovation.

Our results show that collaboration within the green research network contributes significantly to green innovation. By participating in networks, firms can benefit from external collaboration and thus increase their innovative capacity. Both internal and external collaboration are beneficial for EI. However, interregional cooperation appears to be more important because it supports the hypothesis that transregional networks can bridge the knowledge gap even when regions are not geographically close. Furthermore, we find that the participation of private firms is particularly important in driving green innovation and that there is a positive effect from the heterogeneity of the participants that make up the network and the synergies they generate. However, the impact of heterogeneity is non-linear: research groups that are too heterogeneous risk having a negative impact on green innovation.

This study contributes with original insights to the literature on green innovation dynamics within European regions. By examining the role of green networks and the effectiveness of policies aimed at enhancing knowledge diffusion, this paper offers a novel perspective on strategies facilitating the green transition. It introduces several key innovations compared to previous literature. First, we utilize an extensive and up-to-date dataset on green patents at the regional level, allowing for a more detailed and accurate analysis of green innovation across different areas. Second, we highlight the distinct roles played by universities, firms, and public research centers in fostering knowledge exchange. While existing studies focus on the differing green innovation capacities of institutional sectors at the country level, our research examines these differences at the regional level. Third, we look at whether the heterogeneity of the actors involved in the network helps generate new green knowledge proxied by green patents.

The paper is structured as follows. Section 2 discusses the relevant literature and proposes some testable hypotheses. Section 3 describes the methodology and data. A discussion of the econometric results is presented in Sect. 4, and it is followed by the conclusions in Sect. 5.

2 Literature review

A large body of literature has looked at the importance of networks as drivers of innovation (see Powell & Grodal, 2006 for a review of the literature). By facilitating knowledge sharing, networks increase the innovative capacity of individual firms, which alone would not have access to all the knowledge needed to innovate, especially when knowledge is highly complex.

With respect to the standard networks, EI requires multidisciplinary knowledge and large investments in physical and human capital (Cainelli et al., 2015). The literature emphasizes that firms cannot achieve green innovation in isolation. Firms need to seek new knowledge and external expertise by collaborating with other actors (Cisneros et al., 2023).

Empirical analyses support the idea that environmentally innovative firms cooperate more with external partners if compared to other innovative firms (Cainelli et al., 2015; de Marchi & Grandinetti, 2013; Ghisetti et al., 2015). This collaboration is essential for enhancing overall green innovation knowledge and capabilities (Tang et al., 2020). It draws on the idea that environmental innovations require more heterogeneous sources of knowledge with respect to other innovations (Horbach et al., 2013). Consequently, firms are inclined to engage in collaborative efforts with external partners leveraging shared knowledge, resources, and expertise (Fabrizi et al., 2024).

Ghisetti et al. (2015) argued that the open innovation mode (Chesbrough, 2003; Chesbrough et al., 2006) may also be applied in the context of environmental innovation. Given the high and multidisciplinary skills (including technical and scientific skills, legislative skills, and managerial and economic competencies) required for implementing or developing green innovations, external knowledge sourcing and networking becomes crucial for firms (Fabrizi et al., 2018). The first dimension of the open innovation mode is represented by the way firms search for external knowledge in order to innovate and accounts for the breadth of the firm's knowledge search. The greater the number of external parties with which a firm cooperates, the more likely it is to compensate for the lack of some specific internal competence. Moreover, implementing green technologies aims to achieve several goals, including enhancing production efficiency and meeting market and regulatory quality standards (Oltra & Saint Jean, 2005). The extensive networks address these multiple objectives related to EI by leveraging potential economies of scope.

In addition, physical proximity encourages knowledge transfer, as underlined by Boschma (2005). This is particularly relevant because knowledge tends to be geographically concentrated, thus making location a critical factor for efficient knowledge sharing (Eugster et al., 2022). Indeed, the literature highlights that knowledge spillovers from foreign sources can significantly enhance a region's innovative capacity. Spatial knowledge spillovers, especially from neighboring regions, improve the ability to innovate of a specific area (see for instance, Charlot et al., 2015; Kijek & Kijek, 2019).

However, when there is no geographical proximity, transnational networks can also fill this gap as noted by Autant-Bernard et al. (2007) and Maggioni and Uberti (2011). This is based on the idea that regions involved in trans-regional networks are more likely to participate in innovation activities. These trans-regional networks guarantee that a region could still connect to external knowledge flows even in the event of not being close to each other, hence enhancing green innovation activities in such a region. Interactions between local and transregional knowledge networks offer a strong environment for innovation; it is able to draw from both local and foreign knowledge. Given the importance of networks and open innovation for the creation of green knowledge, we use data on European FPs in green fields to investigate their contribution to generating green patents at the regional level. In particular we pose the following research questions:

1. Does collaboration within green research networks promote the green innovation of the regions involved?
2. Does collaboration beyond regional boundaries facilitate the diffusion of knowledge, thus promoting EI?

The use of information on green FPs allows us not only to assess the importance of regional and transregional research networks, but also to consider the role of the different institutional sectors involved in the networks and of their synergies. Empirical and theoretical literature highlights the numerous benefits that can be gained from participating in mixed partnerships (Paier & Scherngell, 2011; Bettina, 2015; Fabrizi et al., 2016). These partnerships offer a set of advantages for all parties involved, such as access to complementary skills, access to larger financial resources, and the reduction of risks. Thus, synergies among different actors (private and public) becomes crucial for driving innovation. In the context of green innovation, the interaction and hybridisation between three institutional spheres—'industry', 'university' and 'government' (Triple Helix, Etzkowitz & Leydesdorff, 2000)—is particularly important due to the heterogeneity of knowledge required for finding green solutions, the role of regulation in directing green efforts and the necessity of adopting a systemic approach. Nevertheless, as highlighted by the literature, the interactions might also present challenges due to the diverse knowledge bases and objectives of each actor, which could potentially reduce the innovation capacity (Foray & Lissoni, 2010; Lovelace et al., 2001). For instance, building on the distinction between knowledge availability and use, Huo et al. (2019) study the possible nonlinearities in the relationship between technological knowledge heterogeneity and innovation.

In this context, we investigate which characteristics of network participants are more important for EI at the local level, studying the contribution of different institutional sectors to the innovation capacity. Moreover, we look at the diversification degree of network actors by using the entropy concept. Specifically, we formulate the last research question:

3. Do institutional sectors contribute differently to increasing green knowledge? Does a high diversification lead to a greater innovation? Is the relationship linear?

On the one hand, different actors can bring different knowledge and skills to the table; on the other hand, different objectives and knowledge bases can create frictions in innovation capacity. The heterogeneity of objectives and approaches, in particular between public institutions focused on broader societal impacts and private companies focused on market-driven applications, can hinder coherent progress and reduce innovation efficiency. Initially, increased diversification can enhance innovation by fostering a rich exchange of ideas and resources. However, as diversification increases, the complexity and potential conflicts between actors may reduce the ability to innovate effectively.

3 Methodology and data

3.1 Data

We collect data covering the period 2003–2021 for 279 European regions[2] on individual green patent applications to account for green innovation, and data on collaborative research projects funded under the FPs to represent green research networks within and between regions.

3.1.1 Green patents in European regions

We rely on microdata from the OECD REGPAT database, focusing on the number of green patents as an indicator of innovative activity. The database collects data

[2] We use the 2016 version of the NUTS2 classification.

held by the European Patent Office (EPO), which contains information on individual patent applications worldwide. We focus on applications filed with the EPO by European applicants, rather than using data on applications filed through the Patent Cooperation Treaty (the PCT). To regionalize individual applications, the address of the inventor is used as it is considered to be a better proxy of the location where the focal technology was developed (Bello et al., 2023). We consider the priority year for each application.

As underlined in Favot et al. (2023), there are different methodologies developed by international organisations to identify patents on environmental-related technologies. In this paper, we apply the "Y02/Y04S tagging scheme" developed by the EPO in collaboration with the United Nations Environmental Programme (UNEP) and the International Centre on Trade and Sustainable Development (ICTSD) to find low-carbon, sustainable, and climate change mitigation technologies (CCMTs). This methodology adds the Y sections to the 8 pre-existing standard sections (A-H) of the Cooperative Patent Classification (CPC). The tagging scheme was introduced to facilitate the identification of mitigation technologies in the energy sector (Veefkind et al., 2012). Later, the scheme was expanded to include all CCMTs covering several categories such as energy, greenhouse gases (GHG) capture, buildings, industry, transport, and waste and wastewater management (Angelucci et al., 2018). Table 1 reports the subclasses (codes) that allow us to identify the technologies relevant to

Table 1 Y02/Y04S Tagging scheme (Favot et al., 2023)

Code	Description
Y02	Technologies or applications for mitigation or adaptation against climate change
Y02A	Technologies for adaptation of climate change
Y02B	Climate change mitigation technologies related to buildings, e.g. housing, house appliances or related end-user applications
Y02C	Capture, storage, sequestration or disposal of greenhouse gases
Y02D	Climate change mitigation technologies in information and communication technologies, i.e. information and communication technologies aiming at the reduction of their own energy use
Y02E	Reduction of greenhouse gas emissions, related to energy generation, transmission or distribution
Y02P	Climate change mitigation technologies in the production or processing of goods
Y02T	Climate change mitigation technologies related to transportation
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management
Y04	Information or communication technologies having an impact on other technology areas
Y04S	Systems integrating technologies related to power network operation, communication or information technologies for improving the electrical power generation, transmission, distribution, management or usage, i.e. smart grids

environmental issues. We classify patents as green if they have at least one of these green patent codes.

We count more than 100,000 green patent applications, corresponding to 10 percent of the total applications in European regions over the period 2003–2021. Figure 1 reports the geographical distribution of the number of patents. The map shows a clear clustering of the data. Core regions are characterised by a higher range of distribution (light red), suggesting a concentration of green innovation in central parts of Europe. Conversely, the peripheries, especially towards the north and some southern regions, show lower activity (light and dark green), indicating fewer patents within these areas. The distribution of green patents closely mirrors the overall distribution of patents across regions (see Fig. 3 in the Appendix). Despite the general trend, certain regions in Bulgaria, northern Greece and central-southern Spain have a significantly higher percentage of green patents compared to their total number of patents. This indicates that these regions, although not leading in terms of total number of patents, have a stronger focus on green technologies in relation to their patenting activity.

To check the strength of our analysis, we also employ the ENV-TECH classification ("Series of patent search strategies for the identification of selected environmental-related technologies") developed by OECD (Haščič & Migotto, 2015). This methodology is based on the International Patent Classification (IPC) and the CPC codes and provides an alternative identification scheme for measuring innovation in

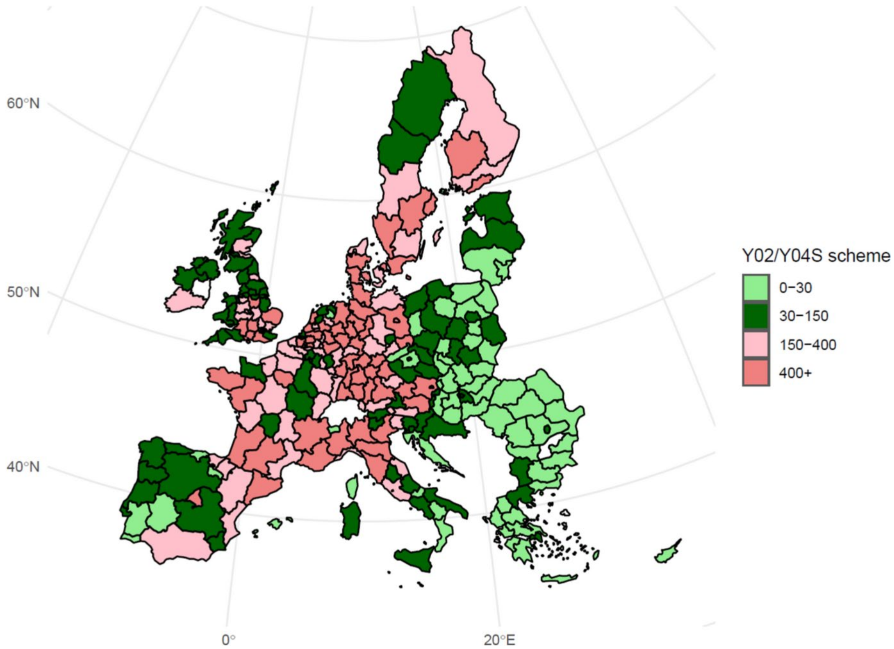

Fig. 1 Distribution of green patents at NUTS2 level. Sum over the period 2003–2021. Authors' calculation is based on the Y02/Y04S scheme

environmental-related technologies. We follow the previous strategy for regionalizing the individual green patent applications.[3]

3.1.2 Green research networks

The second variable of interest accounts for the green networks. To construct and measure the network, we use data on EU-funded research projects that support the formation of transnational collaborations on topics related to the green transition to measure green networks. The EU OPEN DATA PORTAL provides data on joint research projects funded under the Framework Programme (FP) for Research and Technology Development (RTD). We have selected projects with green aspects according to the following thematic priority (Table 2): FP6-SUSTDEV (2002–2006), FP7-ENERGY FP7-ENVIRONMENT FP7-TRANSPORT (2007–2012), and Horizon 2020—SOCIETAL CHALLENGES (2014–2020). As clarified by the European Commission (2010) “The Framework Programmes have included environmental issues since the 1980s but the environmental research programme gained substantial momentum from the 1990s onwards”.[4] The choice of green programme is based on their objectives, as specified in the programming documents, and in particular in those more oriented towards green innovation. We have observed that innovation goals are crucial, and constantly re-proposed in the various FPs, especially in the programs aimed at the transport and energy sectors and in those that can be placed in the more general context of environmental sustainability and the fight against climate change.

These data provide important insights as they include the geographical dimension and the sectoral affiliation of the participants, allowing us to examine the collaboration between regions and across different sectors.

Green network variables are derived from the information on projects funded by FPs. Specifically, we consider the total number of collaborative links within and between regions, represented by the variable *LINKS*. To calculate this variable, we used the information available at project level. Considering n the number of participants in a given project, the potential links (or ties) activated within them, attributed to each individual participant, is equal to $n - 1$. We assume a fully connected network in which all nodes (participants) are interconnected. Then, we attributed this value, or weight (as proxy of actual links) to the regions, so as to obtain a weighted regional network for each project. Finally, to build our panel data, we aggregated (summed) the data from all the projects, by starting year of project and regions. In Fig. 2, we show the total number of collaborations (*LINKS*) for each region. The figure underlines that most of the European regions are more inclined to create networks and some of them, especially in the centre of Europe, are able to pursue environmental innovation. The clusterization is less evident with respect to the patent distribution.

[3] Figure 4 in the Appendix shows the geographical distribution of green patents according the ENV-TECH classification.

[4] For an overview of the FP1– Horizon 2020 (historical basis, main programming documents, resources allocated and thematic areas) see Reillon (2017).

Table 2 Thematic priority of FP programmes

FP—Thematic priority	
FP6—(2002–2006)	SUSTDEV: Sustainable development, global change and ecosystems
FP7—(2007–2013)	ENERGY
	ENVIRONMENT
	TRANSPORT
FP8—Horizon 2020 (2014–2020)	H2020-EU.3.2.—SOCIETAL CHALLENGES—Food security, sustainable agriculture and forestry, marine, maritime and inland water research, and the bioeconomy
	H2020-EU.3.3.—SOCIETAL CHALLENGES—Secure, clean and efficient energy
	H2020-EU.3.4.—SOCIETAL CHALLENGES—Smart, Green and Integrated Transport
	H2020-EU.3.5.—SOCIETAL CHALLENGES—Climate action, Environment, Resource Efficiency and Raw Materials

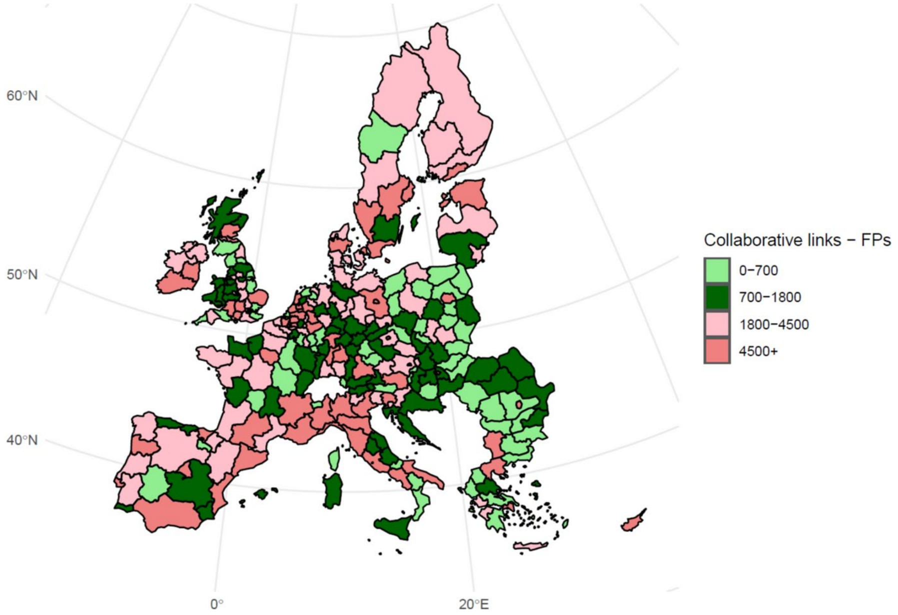

Fig. 2 Number of total collaborations at NUTS2 level. Authors' calculation based on FP-RTD data

The variable *LINKS* is then subdivided into collaborative links among residents within the same region (*INTRALINKS*) and collaborations between residents and external partners (*EXTRALINKS*). Additionally, we gather data on the number of green project participants, categorized by four institutional sectors to account for the composition of private and/or public networks. The variables *PRC*, *HES*, *REC*, and *OTH* correspond to the number of participants from private for-profit entities, higher or secondary education institutions, research centres or organizations, and other sectors, respectively, of a given region, obtained as the sum of all participants belonging to a specific sector/region for all green projects. To analyze in detail the effects of links between companies and universities, as for the variable *LINKS*, starting from the projects, and subsequently attributing the values to the individual regions, we have also calculated the variable *PRC_HES* that measures the amount of links between private for-profit entities and higher or secondary education institutions. See Table 3 for details.

Table 3 Variable description and sources

Variable	Description	Source
PAT	Total number of green patent applications	OECD REGPAT database; own elaboration
LINKS	Total number of region's collaboration links (internal and outer) with other regions	EU OPEN DATA PORTAL; own elaboration
INTRALINKS	Total number of region's internal links	EU OPEN DATA PORTAL; own elaboration
EXTRALINKS	Total number of region's outer (interregional) links	EU OPEN DATA PORTAL; own elaboration
PART	Total number of project participants per region	EU OPEN DATA PORTAL; own elaboration
PRC	Total number of participants belonging to private for-profit entities	EU OPEN DATA PORTAL; own elaboration
HES	Total number of participants belonging to higher or secondary education institutions	EU OPEN DATA PORTAL; own elaboration
REC	Total number of participants belonging to research centres or organizations	EU OPEN DATA PORTAL; own elaboration
OTH	Total number of participants belonging to other	EU OPEN DATA PORTAL; own elaboration
PRC_HES	Total number of links between private for-profit entities and higher or secondary education institutions by regions	EU OPEN DATA PORTAL; own elaboration
RD	R&D total expenditure on GDP	Eurostat regional database
EDU	Ratio of population with tertiary education and total population	Eurostat regional database
POP	Population in thousands	Eurostat regional database

3.2 Empirical approach

To study the relationship between green innovation and networks, we estimate a knowledge production function as in Meliciani et al. (2022) and Di Cagno et al. (2014) at NUTS2 level. The first research question presented in Sect. 2 has been assessed by means of the following econometric model:

$$\ln PAT_{i,t} = \beta_0 + \beta_1 \ln LINKS_{i,t} + \beta_2 RD_{i,t} + \beta_3 EDU_{i,t} + \beta_4 POP_{i,t} + \theta_{m,t} + u_{i,t} \quad (1)$$

In Eq. (1), the dependent variable *PAT* is equal to$(patents + 1)$,[5] where *patents* is the total number of green patent applications identified according the "Y02/Y04S tagging scheme" in each region i at time t. The parameter β_1 captures the correlation between the green innovation and the independent variable *LINKS* that accounts for the green networks, expressed in logarithm. We add a set of controls to account for R&D expenditure, human capital, and size. Specifically, *RD* measures the expenditure on general R&D as a percentage of GDP, *EDU* is a proxy for human capital calculated as the population with tertiary education and the total population, while *POP* accounts for the regional population. The data are taken from the Eurostat regional database (Table 3). The error term is denoted by $u_{i,t}$.

We further control for time-invariant unobservables by considering local specific characteristics that are not captured by other regressors. We include several types of fixed effects in the equation. Specifically, the model in Eq. (1) includes NUTS1 fixed effects by year ($\theta_{m,t}$). This allows us to better account for cross-sectional and temporal heterogeneity and to control for unobservables that may vary over time. In addition, we estimate the model by separately adding country fixed effects and NUTS1 fixed effects. In both estimations, year fixed effects are included to account for time shocks that affect regions simultaneously in a given year. Finally, the model was estimated including country fixed effects by year. However, the more comprehensive approach in Eq. (1) takes into account not only the specific economic characteristics of the macro area, but also idiosyncratic shocks that affect the specific NUTS1 region in a given year, thereby increasing the accuracy and robustness of the estimated relationships between variables.[6]

Furthermore, we examine the role of domestic and external collaborations in Eq. (2), where the variable *NET* represents both *INTRALINKS* and *EXTRALINKS*. To better study the contribution of external collaborations to EI, we introduce *EX_links* (Eq. 3), which is calculated as the ratio of *EXTRALINKS* to the total collaborations. The network variables, except *EX_links*, are expressed in logarithms.

$$\ln PAT_{i,t} = \beta_0 + \beta_1 \ln NET_{i,t} + \beta_2 RD_{i,t} + \beta_3 EDU_{i,t} + \beta_4 POP_{i,t} + \theta_{m,t} + u_{i,t} \quad (2)$$

[5] We follow Berkes & Nencka (2024) for the transformation of the dependent and network variables. We show results using the inverse hyperbolic sine of patents and network variables as an alternative transformation in Tables 10 and 11 in the Appendix. The results are consistent with our baseline estimates.

[6] We excluded NUTS2 fixed effects due to the unbalanced nature of our panel, with limited longitudinal data for some regions. Given that our key variable evolves slowly over time, including NUTS2 FE would absorb much of its variability. As a result, the estimation would become inefficient, and the standard errors would increase significantly.

$$\ln PAT_{i,t} = \beta_0 + \beta_1 EX\_links_{i,t} + \beta_2 RD_{i,t} + \beta_3 EDU_{i,t} + \beta_4 POP_{i,t} + \theta_{m,t} + u_{i,t} \quad (3)$$

$$\begin{aligned}\ln PAT_{i,t} = \beta_0 + \beta_1 \ln PRC_{i,t} + \beta_2 \ln HES_{i,t} + \beta_3 \ln REC_{i,t} + \beta_4 \ln OTH_{i,t} \\ + \beta_5 RD_{i,t} + \beta_6 EDU_{i,t} + \beta_7 POP_{i,t} + \theta_{m,t} + u_{i,t}\end{aligned} \quad (4)$$

$$\begin{aligned}\ln PAT_{i,t} = \beta_0 + \beta_1 entropy_t + \beta_2 entropy_t^2 + \beta_3 \ln PART_{i,t} + \beta_4 RD_{i,t} \\ + \beta_5 EDU_{i,t} + \beta_6 POP_{i,t} + \theta_{m,t} + u_{i,t}\end{aligned} \quad (5)$$

Finally, to respond to the third research question, we analyse the composition effect studying the contribution of different institutional sectors to EI. First, we estimate Eq. (4) and try to understand the role of *PRC*, *HES*, *REC* and *OTH* individually both as number of participants and as dummy variables. Then, we also consider a specific type of collaboration between the private sector and universities (*PRC_HES*). Second, in Eq. (5), we consider the diversification degree of network components. Starting from the literature on team member variety (Huo et al., 2019; Lee et al., 2015; Lovelace et al., 2001), we use the concept of entropy or diversity and calculate the Shannon's index (H), defined as[7]:

$$H = -\sum_{i=1}^{n} p_i ln(p_i) \quad (6)$$

where p_i represents the probability that participant belongs to sector i (PRC, HES, REC, OTH). This entropy, which can be used to measure the dispersion degree in a distribution, reaches its maximum when events are equiprobable (or uniformly distributed). If the value of the index is near zero, the degree of dispersion is lower. The higher the value of H, the greater the diversity. In our setup, an entropy equal to zero corresponds to a concentration of network composition in one of the four modes (*PRC*, *HES*, *REC*, *OTH*). To check the presence of nonlinearities, we add the squared value of entropy index. The number of total network participants (*PART*) is added as a control.
We add a robustness estimation of the models with lagged regressors. As is common in the literature (e.g., Costantini et al., 2015), we consider a lag p equal to one ($p = 1$). The results are reported in Table 9 in the Appendix.

The analysis uses an unbalanced panel dataset. With respect to the original dataset described in Sect. 3.1, observations for which control variables were not available were dropped. This adjustment results in the final sample of the 232 NUTS2 regions observed, on average, for 12.3 years.

[7] To check our results, we also use the Herfindahl index as in Huo et al. (2019). The results, which are available upon request, are qualitatively consistent with those obtained using the Shannon index.

4 Results

In this section, we present the findings from our empirical investigation, which attempts to understand the role of green research networks in enhancing EI in European regions.

Table 4 shows the estimates of the relationship between green patents and the number of internal and external collaborative links of regions (*LINKS*). In column (1), the model is estimated by including country and year fixed effects, while NUTS1 and year fixed effects are included in column (3). Moreover, to control for unobservables over time, we report the results including country fixed effects by year in column (2) and NUTS1 fixed effects by year in column (4). By examining the values of R-squared and Within R-squared, the last specification, which we have identified as the baseline, shows an appropriate compromise in explaining a significant portion of the overall variance and the variance within individual entities over time. We find a positive and significant coefficient of *LINKS* across all specifications (1)–(4). This indicates that the collaboration within the green research network significantly contributes to enhance the green innovation of the concerned areas. This result is consistent with the literature, which identifies networks as key drivers of innovation by enabling the sharing of knowledge and resources that individual firms may lack (Fabrizi et al., 2016, 2024; Ghisetti et al., 2015). By participating in green research networks, firms can benefit from external collaboration, as such innovations require multidisciplinary knowledge and investment in physical and human capital, as well as access to a wider range of resources and markets, thereby enhancing the innovative capacity of firms within the regions. This is in line with the open innovation mode, which emphasises outsourcing knowledge to fill the gap in technical characteristics that are essential for environmental innovation. Moreover, the control variables for R&D expenditure (*RD*), education level (*EDU*), and population size (*POP*) also have significant and positive coefficients, indicating that these factors are crucial for green innovation alongside network collaboration. In Table 12 in the Appendix, for robustness, we present the model's estimates using the "ENV-TECH classification" to identify the dependent variable. The results are quite similar and confirm the strength of our initial analysis.

We then address the second research question about whether collaboration beyond regional boundaries promotes EI, providing further insights by distinguishing between the numbers of a region's internal and external links. In columns (5)–(7), Table 4 reports the estimates of the model with NUTS1 fixed effects by year.[8] We find positive and significant coefficients for *INTRALINKS* and for extra-regional links (*EXTRALINKS*) in column (5) and (6) respectively. This suggests that both types of collaboration are beneficial for green innovation. Intra-regional collaboration enhances local knowledge sharing and innovation capacity, supporting the idea that proximity fosters knowledge transfer. Interregional collaborations, on the other hand, broaden knowledge diffusion and access to diverse expertise and resources. When

[8] Table 7 in the Appendix shows the model's estimates with country and year fixed effects, NUTS1 and year fixed effects, and country fixed effects by year. The estimates confirm the results of the baseline model.

Table 4 Estimates of the relationship between EI and green networks: total, intra, and extra links

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(LINKS_t)$	0.098***	0.107***	0.075***	0.100***			
	(0.017)	(0.020)	(0.013)	(0.019)			
$\ln(INTRALINKS_t)$					0.224***		
					(0.041)		
$\ln(EXTRALINKS_t)$						0.101***	
						(0.019)	
EX_links_t							0.314***
							(0.072)
RD_t	22.899***	23.788***	15.525***	16.033***	15.157***	16.027***	17.137***
	(5.728)	(6.036)	(4.034)	(4.769)	(4.304)	(4.764)	(5.399)
EDU_t	0.023***	0.021***	0.022***	0.018***	0.011**	0.018***	0.027***
	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
POP_t	0.029***	0.028***	0.031***	0.030***	0.027***	0.030***	0.034***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Constant	−0.106	−0.063	0.062	0.086	0.332***	0.090	−0.079
	(0.114)	(0.131)	(0.105)	(0.126)	(0.123)	(0.126)	(0.140)
Country FE	Yes	–	–	–	–	–	–
Time FE	Yes	–	Yes	–	–	–	–
Country by year FE	–	Yes	–	–	–	–	–
NUTS1 FE	–	–	Yes	–	–	–	–
NUTS1 by year FE	–	–	–	Yes	Yes	Yes	Yes
Observations	2860	2736	2855	2517	2517	2517	2517
R-squared	0.814	0.832	0.859	0.893	0.894	0.893	0.889
Within R-squared	0.535	0.559	0.454	0.558	0.562	0.558	0.544

The model was estimated by means of a linear regression with multiple fixed effects. Dropped singleton observations: 124 (2), 5 (3), and 343 (4–7). Standard errors clustered at the regional level in parentheses. ***p<0.01, **p<0.05, *p<0.1

two or more regions are not geographically close, transregional networks can fill the gap in terms of knowledge sharing (Autant-Bernard et al., 2007; Maggioni & Uberti, 2011). Moreover, improving knowledge diffusion can reduce the problem of knowledge concentration in specific advanced areas (Eugster et al., 2022).

Due to collinearity issues, we cannot estimate the model with both intra and extra links simultaneously. Therefore, we compare the contribution of the external collaborations on EI by examining the ratio between the number of external links and total links. The results are presented in column (7), where *EX_links* shows a positive and significant coefficient. Given the total number of collaborations, an increase in the number of external collaborations relative to internal collaborations may contribute positively to enhance the green innovation capabilities of the regions. These results emphasize the importance of the transregional geographical dimension of networks and the idea that cultural proximity, created through the networks, can compensate the geographical proximity for knowledge sharing (Boschma, 2005).

For what concerns the composition dimension, we have highlighted how the literature points to the combination of complementary skills of different network participants for creating significant synergies that can lead to stronger innovation. However, the heterogeneity of network participants can create frictions in the ability to innovate due to different knowledge bases and the *dual use* (business and academic) of new technologies. We address this point by studying first the differential contributions of institutional sectors to EI. Table 5 reports the baseline model's estimates.[9] The coefficient for private for-profit entities (*PRC*) is positive and significant (column 1), suggesting that private sector participation is particularly significant in driving green innovation. In contrast, we do not find significant coefficients for other institutional sectors. When considering the sectors separately however, the higher education sector (*HES*) also shows a positive and significant coefficient (column 6). While the model that includes all sectors together appears to be more suitable for describing the phenomenon, both in terms of overall R-squared and within R-squared, we cannot exclude that the insignificant coefficient of *HES* may be due to the presence of collinearity.[10] Furthermore, consistent results are observed in the models with lagged regressors and the inverse hyperbolic sine transformation (see Tables 9 and 11 in the Appendix, respectively). To check the results, we also consider the dummies *d_PRC*, *d_HES*, *d_REC*, and *d_OTH* assume value one to account for the presence of participants from private for-profit entities, higher or secondary education institutions, research centres or organizations, and other sectors, respectively. We find a positive and significant coefficient for the private sector (column 2). The capability of the private sector in driving green innovation is not surprising since private companies are more interested in patenting for commercialisation than public bodies, and, therefore, it is expected that networks composed of private firms would show a higher propensity for innovation. However, it does not exclude that a heterogeneous network composition is crucial for promoting green innovation. In particular, the positive and significant effect of collaboration between private firms and universities, as captured

[9] The results of the model with country and year fixed effects, NUTS1 and year fixed effects, and country fixed effects by year in Table 8 in the Appendix are consistent with the baseline model.

[10] The correlation coefficient between PRC and HES is 0.69.

Table 5 Estimates of the relationship between EI and green networks: institutional sectors and diversification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(PRC_t)$	0.182***				0.202***					
	(0.044)				(0.047)					
$\ln(HES_t)$	0.079					0.117**				
	(0.049)					(0.052)				
$\ln(REC_t)$	0.009						0.076			
	(0.045)						(0.050)			
$\ln(OTH_t)$	0.003							0.068		
	(0.045)							(0.052)		
d_PRC_t		0.103**								
		(0.045)								
d_HES_t		0.053								
		(0.050)								
d_REC_t		0.045								
		(0.047)								
d_OTH_t		0.043								
		(0.041)								
$\ln(LINKS_t)$		0.115***	0.142***							
		(0.020)	(0.038)							
$\ln(PRC\_HES_t)$			0.051**	0.113***						
			(0.023)	(0.024)						
$entropy_t$									0.042	0.356**
									(0.077)	(0.168)
$entropy_t^2$										-0.279**
										(0.131)
$\ln(PART_t)$									0.222***	0.233***
									(0.066)	(0.065)
RD_t	14.186***	15.663***	15.071***	15.512***	15.330***	14.703***	16.187***	16.865***	14.717***	14.637***
	(4.368)	(4.548)	(4.362)	(4.783)	(4.541)	(5.188)	(5.224)	(5.444)	(4.349)	(4.359)
EDU_t	0.010	0.014***	0.009	0.017***	0.013**	0.021***	0.021***	0.023***	0.008	0.009
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)

Table 5 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
POP_t	0.025***	0.028***	0.025***	0.028***	0.026***	0.030***	0.030***	0.031***	0.024***	0.025***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Constant	0.623***	−0.021	0.201	0.467***	0.552***	0.458***	0.483***	0.429***	0.533***	0.457***
	(0.149)	(0.126)	(0.159)	(0.143)	(0.143)	(0.154)	(0.160)	(0.149)	(0.134)	(0.136)
NUTS1*Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1912	1912	1912	1912	1912	1912	1912	1912	1912	1912
R-squared	0.896	0.894	0.897	0.895	0.896	0.892	0.892	0.891	0.897	0.897
Within R-squared	0.526	0.562	0.531	0.519	0.522	0.508	0.506	0.503	0.528	0.531

The model was estimated by means of a linear regression with multiple fixed effects. 378 dropped singleton observations. Standard errors clustered at the regional level in parentheses. ***p<0.01, **p<0.05, *p<0.1

by the variable *PRC_HES* in column (3), underlines the complementarity of knowledge generated by universities and private firms in promoting green innovation.

Finally, we consider the diversification degree of network actors in each region. In column (9), the estimates suggest a non-significant coefficient of the entropy index. On the contrary, column (10) shows a nonlinear effect with a positive and significant coefficient for the entropy index and a negative and significant coefficient for its squared term. This suggests that the diversification is positively correlated with innovation, but the relationship is nonlinear. The interaction between an overly large number of actors belonging to different sectors increases the complexity and leads to potential conflicts between them, reducing the ability to innovate effectively. The literature highlights that this issue stems from the differing knowledge bases and objectives of each actor (Foray & Lissoni, 2010; Huo et al., 2019).

Therefore, while private actors seem to be the primary drivers of green innovation, there is still a positive effect from the heterogeneity of the participants that make up the network and the synergies they generate. However, given the non-linear nature of the relationship, overly heterogeneous groups risk negatively impacting green patent creation.

5 Conclusions

In this paper we provide empirical evidence of how green research networks promoted by EU FPs enhance the capacity of environmental innovation in European regions.

We start from the hypothesis that firms need to seek new knowledge and expertise beyond their own boundaries by collaborating with other actors for innovating, given the unique nature of green technologies and the specialised knowledge required for EI. In particular, we ask whether the collaborations in and between regions are positively related to EI and assess whether private companies, public research institutions, and universities contribute differently to increasing knowledge, leading to a heterogeneous impact on green innovation. Additionally, we examine the role of diversification on innovation, considering the synergies and challenges of the interaction among different actors.

Our findings support the role of collaboration in green research networks as a driving force for EI in European regions, thus supporting the role of the open eco-innovation mode (Ghisetti et al., 2015) also at the regional level. By participating in networks, regions can benefit from external collaboration and thus increase their innovative capacity. Both internal and external collaborations are beneficial for EI. However, interregional cooperation broadens knowledge diffusion and access to different expertise and resources. Transregional networks can bridge the knowledge sharing gap even when regions are not geographically close, supporting the view that knowledge sharing can be facilitated not only by geographical proximity but also by cultural proximity (Boschma, 2005). This proximity can be facilitated also through the collaboration of heterogeneous actors with different types of knowledge, integrating the applied research and development activities of private companies with the fundamental research carried out in universities (Etzkowitz & Leydesdorff, 2000).

The positive impact of networks involving universities and firms suggest the importance of this type of collaboration for green innovation. However, specific knowledge is required to be able to absorb the technical tacit information from different domains. As underlined in Huo et al. (2019), increasing the heterogeneity of actors in a team can lead to diminishing marginal returns, as the diverse cross-domain knowledge initially increases information processing advantages, but beyond a certain level of diversification can lead to a reduction in invention impact. Thus, while the diversity of participants within a network fosters synergies that eventually lead to an enhanced innovative capacity, in cases of extreme heterogeneity, these are likely to lead to conflicts and lower innovation efficiency (Foray & Lissoni, 2010).

This paper contributes to an already existent stream of literature in this area by empirically testing the influence of green networks on regional innovation capacity. It emphasizes the role EU-supported cooperative initiatives and policies can play in boosting innovation and in contributing to the EU's achievement of climate neutrality by 2050 through green innovation.

While FPs are an important instrument for fostering green innovation, Europe is lagging behind the US and China in terms of industrial green policies. The proposal to introduce a European sovereign fund for financing investments for the twin transition is still far from being realised. The experience of European Framework Programmes where universities, firms and research centres from different European regions collaborate in projects funded by common European resources is a model that can be adapted also to the implementation of green industrial policies.

In most European countries and regions, the main problem still appears to be the low propensity of academic institutions to collaborate with firms and to transform new knowledge into new processes and products. The formation of networks is an important tool for fostering private–public collaborations and stimulating the applicability of new ideas in the commercial sphere. At the same time, the evidence of a non-linear relationship between the heterogeneity of networks and their ability to foster green innovation suggests that policy makers should take into account this aspect when financing research projects with the aim of fostering green innovation. This evidence adds to works studying the relationship between team composition and creativity/innovation (see, e.g. Huo et al., 2019) by focusing on the impact at the regional level of the presence of heterogeneous institutional actors within European FPs, an aspect that was unexplored so far. In order to come with well designed policy suggestions, further evidence on this issue is needed by investigating whether the result can be generalised to all institutional sectors and/or thematic areas within FPs, and by shedding light on the existence of an "optimal" composition of the networks. While this paper sheds light on the role played by green networks in green innovation, further studies could identify the characteristics of the networks that are more beneficial to green innovation by exploring not only the heterogeneity of institutional participants but also of the regions involved in the network. In this regard, a spatial component could be added to capture unobserved factors that may drive green innovation, by exploiting the bilateral relationships between regions participating in networks (see Costantini et al., 2023). Moreover, the heterogeneity of effects across regions with different levels of technological intensity and absorptive capacity could be investigated also with the purpose of identifying the impact of green research networks on the evolution of regional green innovation disparities in the attempt to study the coherence between R&D and regional cohesion policies.

Finally, it is important to highlight that the final objective of European policies is to achieve carbon neutrality while at the same time preserving and possibly enhancing the economic competitiveness of the area. Green innovation should be instrumental to achieve these targets. While there are some studies showing the positive impact of green innovation on countries and firms' economic performance (see for example Banelienė & Strazdas, 2023; Antonioli et al., 2016) and on the reduction of CO2 emissions (Xie & Jamaani, 2022), further research is needed to investigate the direct and indirect (through innovation) role of green networks for helping regions to achieve the economic and social targets of the green transition.

Appendix

See Table 6 and Figs. 3, 4.

Table 6 Variable descriptive statistics

Variable	Mean	Std. Dev	Min	Max
PAT	20.21	42.56	0.00	499.00
LINKS	197.35	350.73	0.00	4264.00
INTRALINK	13.54	29.06	0.00	444.00
EXTRALINKS	183.81	322.89	0.00	3820.00
PRC	5.57	12.66	0.00	197.00
HES	2.80	4.77	0.00	45.00
REC	3.00	9.05	0.00	145.00
OTH	1.94	6.73	0.00	146.00
PRC_HES	24.71	47.14	0.00	624.00
RD	0.01	0.01	0.00	0.13
EDU	27.15	10.10	6.10	74.70
POP	18.24	15.14	0.26	123.49

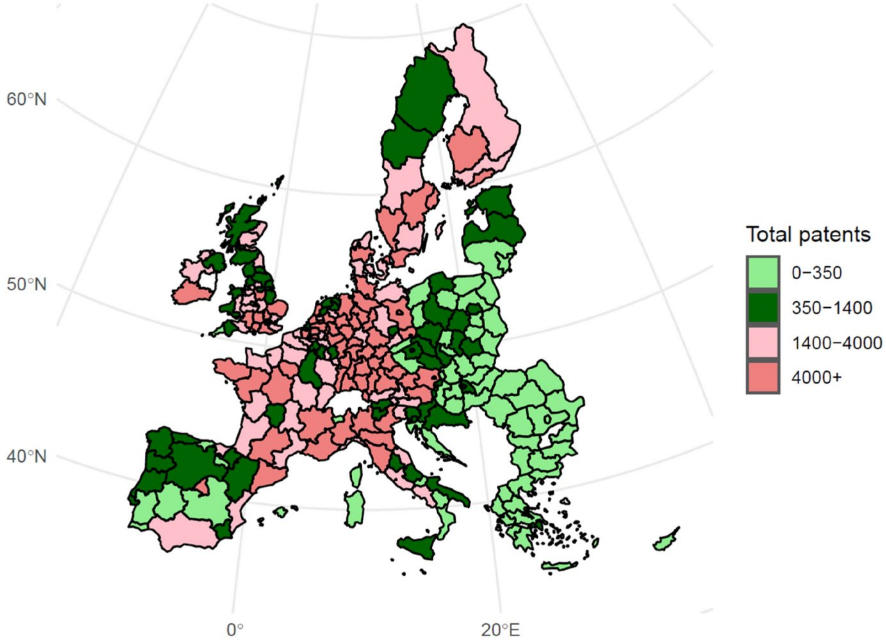

Fig. 3 Distribution of total patents at NUTS2 level. Sum over the period 2003–2021. Authors' calculation

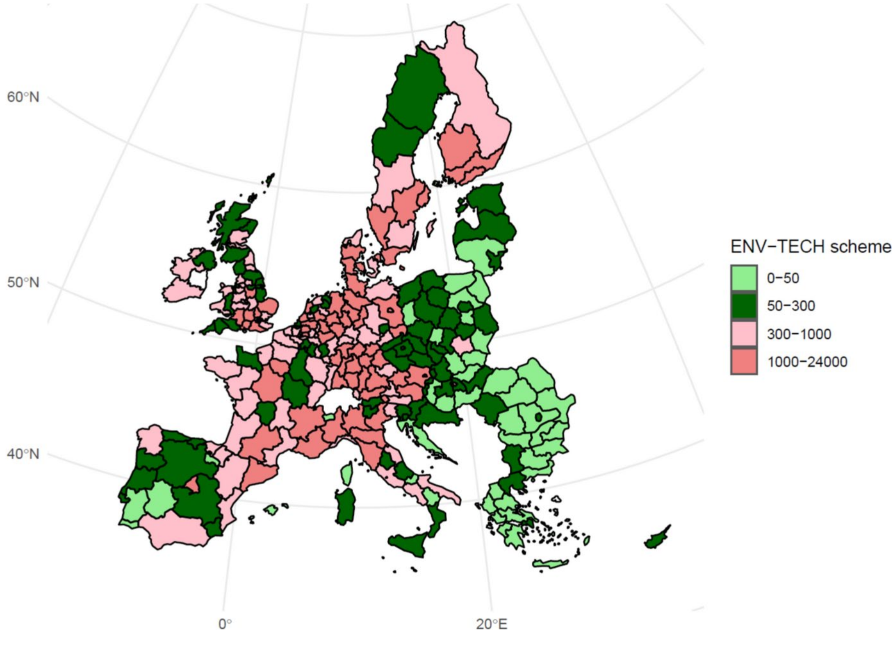

Fig. 4 Distribution of green patents at NUTS2 level. Sum over the period 2003–2021. Authors' calculation based on the ENV-TECH classification

See Tables 7, 8, 9, 10, 11 and 12.

Table 7 Estimates of the relationship between EI and green networks: intra and extra links

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\ln(INTRALINKS_t)$	0.209***	0.239***	0.154***						
	(0.038)	(0.046)	(0.027)						
$\ln(EXTRALINKS_t)$				0.099***	0.108***	0.076***			
				(0.018)	(0.020)	(0.013)			
EX_links_t							0.300***	0.332***	0.231***
							(0.065)	(0.075)	(0.049)
RD_t	22.452***	23.255***	15.029***	22.896***	23.788***	15.512***	24.134***	25.049***	16.490***
	(5.381)	(5.606)	(3.818)	(5.730)	(6.039)	(4.029)	(6.262)	(6.624)	(4.412)
EDU_t	0.016***	0.011*	0.018***	0.023***	0.021***	0.022***	0.032***	0.031***	0.028***
	(0.005)	(0.007)	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)
POP_t	0.026***	0.025***	0.029***	0.029***	0.028***	0.031***	0.033***	0.033***	0.034***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.139	0.233	0.222**	−0.103	−0.059	0.065	−0.250**	−0.247*	−0.037
	(0.119)	(0.142)	(0.103)	(0.114)	(0.131)	(0.105)	(0.123)	(0.139)	(0.113)
Country FE	Yes	–	–	Yes	–	–	Yes	–	–
Time FE	Yes	–	Yes	Yes	–	Yes	Yes	–	Yes
Country by year FE	–	Yes	–	–	Yes	–	–	Yes	–
NUTS1 FE	–	–	Yes	–	–	Yes	–	–	Yes
Observations	2860	2736	2855	2860	2736	2855	2860	2736	2855
R-squared	0.815	0.835	0.860	0.814	0.832	0.859	0.809	0.827	0.857
Within R-squared	0.539	0.566	0.455	0.535	0.559	0.454	0.523	0.546	0.445

The model was estimated by means of a linear regression with multiple fixed effects. Dropped singleton observations: 124 (2)-(5)-(8) and 5 (3)-(6)-(9). Standard errors clustered at the regional level in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 8 Estimates of the relationship between EI and green networks: institutional sectors and diversification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\ln(PRC_t)$	0.199***	0.252***(0.047)	0.084***						
	(0.040)		(0.027)						
$\ln(HES_t)$	0.006	0.030	0.038						
	(0.043)	(0.051)	(0.033)						
$\ln(REC_t)$	0.020	0.016	0.030						
	(0.043)	(0.049)	(0.033)						
$\ln(OTH_t)$	−0.007	−0.020	−0.004						
	(0.033)	(0.041)	(0.028)						
$entropy_t$				−0.001	−0.026	0.076	0.223	0.271*	0.196*
				(0.062)	(0.068)	(0.051)	(0.142)	(0.156)	(0.118)
$entropy_t^2$							−0.194*	−0.258**	−0.106
							(0.115)	(0.127)	(0.091)
$\ln(PART_t)$				0.208***	0.262***	0.119***	0.214***	0.270***	0.122***
				(0.055)	(0.066)	(0.042)	(0.055)	(0.065)	(0.042)
RD_t	18.685***	18.878***	13.996***	18.856***	19.599***	13.970***	18.699***	19.425***	13.921***
	(4.961)	(4.984)	(3.995)	(4.842)	(4.934)	(3.914)	(4.877)	(4.989)	(3.923)
EDU_t	0.020***	0.014*	0.020***	0.017***	0.011	0.018***	0.018***	0.012*	0.018***
	(0.006)	(0.007)	(0.004)	(0.006)	(0.007)	(0.004)	(0.006)	(0.007)	(0.004)
POP_t	0.025***	0.023***	0.029***	0.025***	0.023***	0.028***	0.025***	0.024***	0.028***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Constant	0.302**	0.439**	0.420***	0.212*	0.336**	0.349***	0.154	0.258*	0.320***
	(0.141)	(0.169)	(0.120)	(0.121)	(0.141)	(0.114)	(0.129)	(0.154)	(0.112)
Country FE	Yes	–	–	Yes	–	–	Yes	–	–
Time FE	Yes	–	Yes	Yes	–	Yes	Yes	–	Yes
Country by year FE	–	Yes	–	–	Yes	–	–	Yes	–
NUTS1 FE	–	–	Yes	–	–	Yes	–	–	Yes
Observations	2290	2170	2284	2290	2170	2284	2290	2170	2284

Table 8 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R-squared	0.815	0.839	0.858	0.814	0.838	0.859	0.815	0.839	0.859
Within R-squared	0.509	0.541	0.415	0.507	0.536	0.419	0.508	0.538	0.420

The model was estimated by means of a linear regression with multiple fixed effects. Regarding Eq. (4), results for individual sectors, dummies, and *PRC_HES* with country and year fixed effects, NUTS1 and year fixed effects, and country fixed effects by year are available upon request. Dropped singleton observations: 120 (2)-(5)-(8) and 6 (3)-(6)-(9). Standard errors clustered at the regional level in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 9 Estimates of the relationship between EI and green networks: total, intra, and extra links. Lag equals to 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(LINKS_{t-1})$	0.104*** (0.021)					0.110*** (0.024)	0.074* (0.044)	
$\ln(INTRALINKS_{t-1})$		0.229*** (0.050)						
$\ln(EXTRALINKS_{t-1})$			0.105*** (0.022)					
EX_links_{t-1}				0.393*** (0.083)				
$\ln(PRC_{t-1})$					0.177*** (0.046)			
$\ln(HES_{t-1})$					0.119** (0.053)			
$\ln(REC_{t-1})$					-0.021 (0.050)			
$\ln(OTH_{t-1})$					-0.016 (0.052)			
d_PRC_{t-1}						0.108** (0.051)		
d_HES_{t-1}						0.093 (0.056)		
d_REC_{t-1}						– 0.071 (0.051)		
d_OTH_{t-1}						– 0.004 (0.052)		
$\ln(PRC\_HES_{t-1})$							0.077*** (0.024)	0.108*** (0.025)
RD_{t-1}	18.520** (7.406)	18.129*** (6.466)	18.537** (7.408)	18.891** (8.622)	15.675** (6.397)	18.037** (7.309)	17.193** (6.771)	17.056** (7.218)
EDU_{t-1}	0.018*** (0.005)	0.010* (0.006)	0.018*** (0.005)	0.027*** (0.005)	0.012 (0.007)	0.016*** (0.006)	0.012** (0.006)	0.017*** (0.005)

Table 9 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POP_t	0.028***	0.025***	0.028***	0.031***	0.022***	0.027***	0.024***	0.026***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Constant	−0.162	0.076	−0.158	−0.358**	0.346**	−0.253*	0.106	0.243*
	(0.132)	(0.131)	(0.132)	(0.148)	(0.159)	(0.137)	(0.166)	(0.140)
NUTS1 by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1778	1778	1778	1778	1307	1307	1307	1307
R-squared	0.859	0.860	0.859	0.857	0.873	0.861	0.872	0.871
Within R-squared	0.567	0.569	0.567	0.559	0.525	0.572	0.521	0.517

The model was estimated by means of a linear regression with multiple fixed effects. The results obtained with country and year fixed effects, NUTS1 and year fixed effects, and country fixed effects by year are available upon request. Dropped singleton observations: 221 (1)-(4) and 255 (5)-(8). Standard errors clustered at the regional level in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 10 Estimates of the relationship between EI and green networks: inverse hyperbolic sine transformation

	(1)	(2)	(3)	(4)
$LINKS_t$	0.106***			
	(0.020)			
$INTRALINKS_t$		0.225***		
		(0.040)		
$EXTRALINKS_t$			0.107***	
			(0.020)	
EX_links_t				0.406***
				(0.087)
RD_t	16.411***	15.347***	16.400***	17.603***
	(5.189)	(4.644)	(5.182)	(5.869)
EDU_t	0.025***	0.016***	0.025***	0.034***
	(0.006)	(0.006)	(0.006)	(0.006)
POP_t	0.035***	0.031***	0.035***	0.039***
	(0.004)	(0.004)	(0.004)	(0.005)
Constant	0.122	0.401***	0.126	−0.054
	(0.150)	(0.146)	(0.150)	(0.167)
NUTS1 by year FE	Yes	Yes	Yes	Yes
Observations	2517	2517	2517	2517
R-squared	0.886	0.888	0.887	0.884
Within R-squared	0.538	0.544	0.539	0.526

The model was estimated by means of a linear regression with multiple fixed effects. The results obtained with country and year fixed effects, NUTS1 and year fixed effects, and country fixed effects by year are available upon request. 343 dropped singleton observations. Standard errors clustered at the regional level in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Table 11 Estimates of the relationship between EI and green networks: institutional sectors and diversification. Inverse hyperbolic sine transformation

	(1)	(2)	(3)	(4)	(5)	(6)
PRC_t	0.170***					
	(0.041)					
HES_t	0.074*					
	(0.043)					
REC_t	0.017					
	(0.040)					
OTH_t	0.010					
	(0.040)					
d_PRC_t		0.138**				
		(0.055)				
d_HES_t		0.068				
		(0.059)				
d_REC_t		0.067				
		(0.054)				
d_OTH_t		0.045				
		(0.049)				
PRC_HES_t			0.048**	0.108***		
			(0.023)	(0.024)		
$LINKS_t$		0.125***	0.167***			
		(0.022)	(0.044)			
$entropy_t$					0.050	0.341*
					(0.093)	(0.202)
$entropy_t^2$						−0.256*
						(0.157)
$PART_t$					0.226***	0.231***
					(0.067)	(0.066)
RD_t	14.338***	15.892***	15.332***	15.912***	14.912***	14.864***
	(4.677)	(4.887)	(4.717)	(5.235)	(4.691)	(4.712)
EDU_t	0.014*	0.019***	0.013**	0.023***	0.012*	0.013*
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
POP_t	0.028***	0.033***	0.029***	0.033***	0.028***	0.028***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.807***	-0.023	0.197	0.600***	0.641***	0.567***
	(0.173)	(0.153)	(0.201)	(0.168)	(0.158)	(0.161)
NUTS1 by year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1912	1912	1912	1912	1912	1912
R-squared	0.891	0.888	0.892	0.889	0.891	0.892
Within R-squared	0.505	0.543	0.510	0.497	0.508	0.510

The model was estimated by means of a linear regression with multiple fixed effects. The results obtained with country and year fixed effects, NUTS1 and year fixed effects, and country fixed effects by year are available upon request. 378 dropped singleton observations. Standard errors clustered at the regional level in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Table 12 Estimates of the relationship between EI and green networks: ENV-TECH classification

	(1)	(2)	(3)	(4)
$\ln(LINKS_t)$	0.118***	0.129***	0.091***	0.122***
	(0.021)	(0.025)	(0.017)	(0.024)
RD_t	25.512***	26.228***	15.904***	15.907***
	(6.548)	(6.793)	(4.351)	(5.023)
EDU_t	0.023***	0.021***	0.023***	0.019***
	(0.006)	(0.007)	(0.005)	(0.007)
POP_t	0.036***	0.036***	0.040***	0.038***
	(0.004)	(0.004)	(0.004)	(0.005)
Constant	0.235*	0.262	0.408***	0.414**
	(0.142)	(0.159)	(0.137)	(0.165)
Country FE	Yes	–	–	–
Time FE	Yes	–	Yes	–
Country by year FE	–	Yes	–	–
NUTS1 FE	–	–	Yes	–
NUTS1 by year FE	–	–	–	Yes
Observations	2860	2736	2855	2517
R-squared	0.773	0.794	0.818	0.862
Within R-squared	0.474	0.498	0.387	0.491

The model was estimated by means of a linear regression with multiple fixed effects. Dropped singleton observations: 124 (2), 5 (3), and 343 (4). Standard errors clustered at the regional level in parentheses. ***p<0.01, **p<0.05, *p<0.1

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